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Student´s social e-reputation ("karma") as motivational factor in MOOC learning

LONG TITLE:

The social e-reputation of the student ("karma") as a motivational factor for success in learning via MOOCs

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The social e-reputation of the student ("karma") as a motivational factor for success in learning via MOOCs

In this paper, we analyse the role of the student's digital reputation as a motivational factor for successfully completing Massive Open Online Courses (MOOCs). After a review of the academic literature on the role that the student's reputation plays in community learning and to understand the role that new techniques of gamification have in virtual learning to involve the student, an empirical analysis is performed on the basis of data from a pioneer MOOC of Social Entrepreneurship. Evaluating the results, we conclude that social reputation is a key factor for the student in successfully completing the course, and that the student's retention is, along with his e-reputation ("karma"), directly related to his degree of participation, the rewards received, and his correspondence with peers. This shows that one of the factors that explain the student's MOOC completion, is his degree of interaction with other students and mainly his reputation among them.

Keywords: MOOC; gamification; karma; distance education; learning communities

Introduction

The use of MOOCs as a learning tool provides a rich and varied learning environment characterized by the interaction of students who come from different places. Its participatory, open and innovative nature provides new ways to learn in virtual learning environments. It is a learning network enriched by the interaction among participants working on-line, and using the new capabilities and peculiarities of digital learning environments.

Vázquez, López & Sarasola (2013) note that the lack of activities that foster the creation of learning communities through collaborative, participatory work is an important factor in the high drop-out rate of MOOCs. Moreover, as Sosa, López & Díaz (2014, p. 3) indicate, in analysing the role of learning communities and collaborative work as features of MOOCs, "people must think about, discuss and share information and content by way of permanent communication". In this case, the value is not so much in the content as in the creation of the community that forms as a result of the interest in a given subject (Vázquez & Sevillano, 2011). Thus, a community that gives feedback and helps each of its members in the teaching and learning process is created.

In this social setting of a learning community, there immediately arises the need to understand the role and the position that each student assumes in relation to "the others": in the interaction with students and the instructor. Thus, concepts like "reputation" or "status" arise as part of the way to relate to the community in which one learns. Despite both terms have too often been used interchangeably (Vassileva, 2012) the difference between "status" and "reputation" is that status might be achieved by the user on her own, while reputation is based on the opinion of others about the contributions of a user. Reputation is a longitudinal social evaluation of a person's actions. It is not a characteristic that an individual has, but rather the characteristics that others think he has (Hendrikx, Bubendorfer & Chard, 2015). As such, reference to the collective is decisive.

General theories about learning (Ramos, 2013) and learning in virtual environments (for a review of the literature, Peltier, Drago & Schibrowsky, 2003) have identified reputation as a motivational factor in this kind of learning. In the context of MOOCs, motivation has been identified as an important element which contributes to the involvement of the student (Milligan, Margaryan & Littlejohn, 2013), but the factors that stimulate this involvement have for the most part been ignored, as Liyanagunawardena, Adams & Williams (2013, p. 219) acknowledge in their bibliographical study which reviews literature about MOOCs: "One can speculate about an individual's motivation to participate in a MOOC: the desire to achieve an academic credential at a reduced cost, personal enrichment, and/or self satisfaction. However, why individuals participate in MOOCs has yet to be explored. It would be valuable to learn about the actual motivations in place, the percentage of participants taking up MOOCs for those reasons, and to know how those motivations might vary from one course or discipline or even provider to another".

This need to better understand the real reasons that motivate the student in MOOCs makes us wonder, as a research question, what role the student's reputation, or e-reputation within the context of digital environments, plays as a motivational factor to complete the learning through this type of course.

This study delves into this issue at a time when another interesting phenomenon is occurring: the incorporation and spread of gamification tools in learning environments (Jen-Wei & Hung-Yu, 2016). These tools are designed to improve interaction and communication with the community and improve the learning experience, underscoring the prominence of motivational elements based on aspects like reputation, grades or degree of completion and closely tied to rewards that reinforce behaviour (Borrás-Gené, Martinez-Nuñez & Fidalgo-Blanco, 2015). In addition, gamification presents a new way to evaluate the reputation of the student, a method linked to aid recognition and relationships with other students: karma.

In the following sections, we review the literature on reputation as a motivational factor and we relate it to the phenomenon of gamification, which is influencing ways to motivate learning, and the role of karma in this context. To complete this study, we performed a full empirical analysis based on data from a pioneer MOOC. We used different methods to assess the impact that interaction and reputation among students have on motivation and success in the experience of learning with MOOCs. We determined the limitations of the study and drew some conclusions in this regard in the last section of the article.

The Reputation of the Student as a Motivational Factor in Learning

Motivational factors have been studied extensively by different disciplines for a long time. According to Santrock (2002), we can find three fundamental theoretical perspectives on motivation, outlined below:

1) Cognitive perspective: emphasizes the power of thought as the motor at work. Santrock (2002) claims that in the specific case of the person who studies, it is her thoughts which guide her level of motivation.

2) Behavioral perspective: underscores the role of rewards in motivation. Different types of reinforcement, in the behaviorist tradition, are included in this category.

3) Humanistic perspective: based on the abilities of the human being to develop. In this area, Marlow's theory of needs (1954) is included. In an analysis of need for esteem, Maslow distinguishes a lower category which includes the respect of others, the need for status, fame, glory, recognition, attention, reputation and dignity, and a higher category, which determines the need for self-respect, including feelings like confidence, competence, achievement, independence and freedom. In this context, McClelland (1985) stresses the need for achievement, the need for belonging and the need for power.

Though the aim of this article is not to review these theories in detail, it is important for the purposes of this study to identify the difference between "extrinsic" and "intrinsic" motivation (Pekrun, 1992). "Extrinsic" motivation comes from outside, through rewards or pressure from the environment on individuals, and "intrinsic" motivation arises from inside, out of the interest or enjoyment that the subject takes in an activity. According to Santrock (2002), the behavioural perspective places emphasis on the importance of extrinsic motivation, since this entails some external incentives like rewards and punishments, and the humanistic and cognitive perspectives highlight the importance that intrinsic motivation has on achievement, which is based on internal factors like self-determination, investigation, challenge and effort. Although this classification has engendered criticism and alternatives (Vasilleva, 2012), it serves to highlight the importance of rewards and external reinforcement, along with internal motivation to achieve success and helping others, as important factors in motivation and success in the experience of learning.

Maslow and the theories of social psychology insist on the human being's need to achieve social recognition and status, and also Bandura's theory on self-efficacy (1997) considers that recognition and status are ways of identifying a skill as one of the sources of self-efficacy. As for the assessment of reputation, it might be measured implicitly (for example, by analyzing the content produced) or explicitly (for example, through ratios or rewards). This information (grades, reinforcements, medals, etc.) is feedback for others to know whether or not they can trust the individual (Dron and Ostashewski, 2015).

When we analyze motivation from the sphere of virtual and on-line learning, different lines of research arises, always interested in the social component: The Community of Inquiry framework (Garrison, 2007) identifies social presence, teaching presence and cognitive presence as elements to build an effective online learning community; Computer-supported collaborative learning (CSCL) research studies pedagogical and technological elements within online collaborative learning groups (e.g., Kreijns et al, 2007) and investigates the interaction between the different involved actors. Social Learning Analytics (SLA), a distinctive subset of Learning Analytics, is coming into play in order to measure this kind of networked interaction. SLA draws on the substantial body of work demonstrating that new skills and ideas are not solely individual achievements, but are developed, carried forward, and passed on through interaction and collaboration (Buckingham & Ferguson, 2012). In this regard, it can be observed that, on the basis of the literature review by Peltier et al. (2003), the most important factors in the effectiveness of education are related to communication and interpersonal relations (interactions among students, student-instructor interaction and instructor support) and aspects related to the design of the course (content, structure and access technology). Marks, Sibley & Arbaugh (2005) corroborated these results, finding especially significant effects in interaction with the instructor and among students. Later studies reinforce the conclusion that interaction among students and with the instructor is decisive (Hone & El Said, 2016).

Among the most commonly identified factors related to motivation in the case of MOOCs are the clear intention of the student to finish the course, the fact that learning is focused on a problem, the accessibility and involvement of the instructor, active learning, interaction with other students and the availability of appropriate resources (Lee & Hammer, 2011; Tobarra, et al., 2014; Hone & El Said, 2016). Emphasis is placed on the importance of interaction among students and with the instructor as central aspects for acquiring knowledge and developing cognitive skills in MOOCs (Zhang, Skryabin & Song, 2016). However, according to Jen-Wei & Hung-Yu (2016), most of MOOCs fails at achieving a learning experience that is rich in content and effective. This is because, according to these authors, they do not offer an experience that involves, motivates and engages the student. In any event, in these analyses of motivational factors in MOOCs, there are no clear references to the role that "reputation among students" plays beyond the interaction and relationships among the actors.

Gamification in Learning with MOOCs: Rewards and Karma

The term "gamification" was coined by Nick Pelling in 2002 (Marczewski, 2013) as the application of game metaphors for real-life tasks that influence behavior and improve the motivation and commitment of the people involved. Deterding et al. (2011) define gamification as the use of elements of game design to improve the immersion, commitment and experience of the user in a non-game context. Gamification works essentially as entertainment which contributes to the enjoyment of participants, who actively become involved with the rest of the learning community through rewards, reputation points or other interactive mechanisms (Gasland, 2011).

Gamification is rapidly being implemented in the field of education, and there are already numerous experiences and analyses of its appropriateness for motivating the student and fostering his involvement (Kapp 2012; Simões, Redondo & Vilas, 2013; Lee & Hammer, 2011). Gamification emerges as a strategy capable of improving the level of student activity, increasing the involvement of the student in the complete learning process (Pedro et al., 2015; Yildirim, 2017), but other quantitative analysis suggests that cognitive impact of gamification over students is not very significant (Domínguez et al., 2013).

As in the researches about motivational factors, the impact of gamification on three types of interaction in MOOCs is studied: student-instructor, student-student and student-content (Jen-Wei & Hung-Yu, 2016). According to these authors, in studying the impact of gamification from the point of view of interaction between student and instructor, it is observed that the process stimulates, improves and maintains the level of the student's commitment to the course (Ryan and Deci, 1996; Hsu, Wen & Wu, 2009). In the case of integration among students, in situations like tutoring in pairs or working in teams, it can improve normal participation (Halavais, 2012; Choi & Kim, 2004; Chen, Sun & Hsieh, 2008). In interaction with content, gamification can improve and promote commitment to the material or be applied to solve problems (Reeves & Read, 2009).

Gamification incorporates an interactive, on-line design which drives a certain competitive effort in the person and incorporates the use of rewards to guide action and promote a sense of achievement and involvement in the group (Deci & Ryan, 2008; Pedro et al., 2015). Rewards in the context of gamification can be related to extrinsic motivations (Hsu, Wen & Wu, 2009), for example, by rewarding behaviour oriented to the solution of problems, and also to intrinsic motivations in fostering self-fulfilment (Lee & Hammer, 2011).

The use of medals (badges) to drive participation and collective learning already aroused the interest of researchers (Knight & Casilli, 2012) beyond the context of gamification, as their use fosters participative learning and demonstrates collaboration. According to Pedro et al. (2015) and Antin & Churchill (2011), the adoption of medals in an educational setting could be a source of motivation and transformation in learning through the democratization of learning and the promotion of learning "for one's whole life" in giving value to what is learned, or by promoting alternative methods of assessment, improving commitment and motivation, reputation, self-fulfilment and identification with the group.

Furthermore, Vassileva (2012) notes that, although reputation has been used for a long time in on-line communities to motivate participation, the specific concept of karma was introduced in the 1990s to reward positive comments with visibility and influence in the community. Karma can be defined as the recognition that the community gives to the user for their contributions in the space of debate. It is a notion of reputation acquired during the development of the course, linked to a social or group area, but related to the subject's contribution to the learning of the community. Thus, it is related to the collaborative learning that emerges through the shared understanding of several students by the interaction of some with others, promoting group skills like communication, listening and participation. Students acquire "karma" points helping the community by contributing stories, by posting comments of quality or by moderation. Karma is affected by consistent and regular participation over long periods of time. This mechanism can promote the creations of a core group of learners actively and deeply participated in all these sharing practices: their behaviour enabled 'vicarious' learning and enhanced the entire learning experience for the broader community, as suggested by Walji, Deacon & Czerniewicz (2016).

Despite this, karma is rarely mentioned in academic literature on education (Portmess, 2013; Ventura, Bárcena & Martín-Monje, 2014) and there are no studies focused on or quantitative empirical analyses devoted to its measurement, evaluation and influence, which is why a specific study like this one is of special interest.

Data and Sample Space

The course we based the study on is the first MOOC about entrepreneurship and social innovation, conducted in Spanish, and launched by one large University in Spain in 2013. It was created to explain, in an enjoyable and thorough manner, the concept of social innovation and the steps to follow to develop a project of this sort. More than half the students were Spanish, or at least accessed the course from Spain. Other countries from which a large number of students accessed the course were Latin American: Chile, Colombia, Mexico, Peru and Argentina. As a result, the native language of the great majority of participants was Spanish.

The course was structured in six different modules and lasted 12 weeks. Its design was planned so that students completed each module in 15 days, although access to all the content was possible from the start to provide participants with a flexible methodology in which they could choose the volume of work and progress at their own pace. The general organization of the course included some teaching videos which explained the content of each subject along with some guided learning mechanisms which oriented the student during the learning process. In the control tests, they received specific feedback via a self-correction mechanism. This way, if a student gave an incorrect answer or was not sure about an answer, he had the option of reviewing the module in question.

Interaction was the key in the design of the MOOC. As a result, the course designers sought to foster collaborative learning in the forum by encouraging comments from the students through motivational messages and the use of different types of badges, karma and votes on comments and students´ answers.

The course had a total of 5,016 registered students, 3,250 of whom actually started it and 711 of whom completed it. 3,250 observations were collected, that is, one record for each student who attended the course, including data about behaviour, activity (on-line activity, posts, votes and on-line answers, mainly) and results (participation, completion and rewards).

We proceeded to analyze the degree of completion of the MOOC (which is linked directly to the student's remaining on the course and is also a measure of his achievement) and related it to the student's activities during the course: messages produced, messages voted on by other students, answers made to comments of other students, the votes these answers received, and votes cast by the student for answers and messages of other students. We have also included another series of variables related to the incentives that the other students receive for advance and achievement in the course (badges or medals, and karma points). These variables reflect their degree of participation and involvement in the MOOC and are indicative of the interaction that they have with the rest of the students.

Despite the obvious decreasing involvement, we will see that success in the course is related to the degree of student participation, rewards and student reputation.

Methods of Analysis and Results

For developing our analysis, we use two statistical methods: classification and regression trees and principal component analysis. Before applying them, we include as preliminary analysis a simple OLS regression that relates the degree of the student's progress (the dependent variable) to participation and rewards in their different forms, and it is observed that the degree of completion of the course (and, ultimately, the final grade), is related directly to her degree of participation and karma.

We corroborate this empirically by observing the significance of variables like votes given to messages from other students, messages sent, votes on student comments, messages and replies (as shown in Table 1). In addition, the role that karma plays in the degree of progress can be observed.

In this regard, we observe in the model above the significant relationship between the student's the degree of completion or grade, and the rewards and recognition that she obtained for her participation and good achievement.

To make a statistically robust analysis from the initial OLS conclusions, we include in next sections the details of two other statistical methods: classification and regression trees and principal component analysis.

Table 1. OLS, using observations 1-3250

Dependent variable: Progress (%)

	coefficient	**std. deviation**	**t-statistic**	**p-value**
Votes for posts	-116.519	257.396	-45.268	<0.00001
Votes for answers	127.753	135.868	0.9403	0.34715
Messages	281.208	514.279	54.680	<0.00001
Messages with vote	-164.029	16.005	-10.249	0.30551

Total votes received	-954.448	146.406	-65.192	<0.00001
Answers	0.60336	0.948558	0.6361	0.52477
Answers with vote	-17.63	123.414	-14.285	0.15324
Karma	658.991	0.619142	106.436	<0.00001
Total votes	-670.253	126.304	-53.067	<0.00001
Gold medals	346.564	504.628	0.6868	0.49228
Silver medals	-258.952	118.375	-21.876	0.02877
Bronze medals	337.093	550.032	61.286	<0.00001

Source: compiled by the authors. n= 3250.

Analysis through Classification and Regression Trees and Principal Component Analysis

Classification and regression trees (CARTs) are a consistent technique in discovering (conditional) relationships among a large number of explanatory covariates, X_i, and a qualitative or continuous dependent variable Y. They are called classification trees when they are applied to qualitative dependent variables and regression trees when the dependent variable is continuous. These techniques (Breiman et al., 1993) involve the application of an algorithm that divides the sample into sub-groups, such that heterogeneity (called node impurity) is minimized in the newly-formed groups. This makes it possible to arrange, in order of importance, the covariates X_i, which allows us to select only a few explanatory covariates (García Pérez, 2009).

Principal component analysis (PCA) is a statistical method (Hotellin, 1933) that describes the variation produced by the observation of random variables p in terms of a set of new uncorrelated variables (called principal components), each of which is a linear combination of the original variables. These new variables are obtained in order of importance, such that the first principal component incorporates as much of the variation due to the original variables as possible. The second principal component is chosen so that it explains as much of the remaining variation as possible that is not explained by the first principal component, subject to the condition of being uncorrelated with the first principal component, and so on, in succession (García Pérez, 2014).

Results and Discussion

In this particular case, in applying classification and regression tree analysis, a regression tree is built, and we have a response variable *Y* (in this case, continuous and non-qualitative) and twelve explanatory variables (X_i). The statistical problem consists of establishing a relationship between *Y* and the X_i. The response variable to analyze, in this case, is the percentage of progress in the course (*progress_percentage*). The variables ($X_1, \ldots, X_{12}$) that, according to their values, might predict the values of *Y* will be, in our case: Votes for posts, Votes for answers, Messages, Messages with vote, Total votes received, Answers, Answers with vote, Karma, Total votes, Gold medals, Silver medals and Bronze medals. The statistical programming environment chosen was R. The result obtained is compiled below in table 2:

Table 2. CART, using observations 1-3250

Dependent variable: Progress (%)

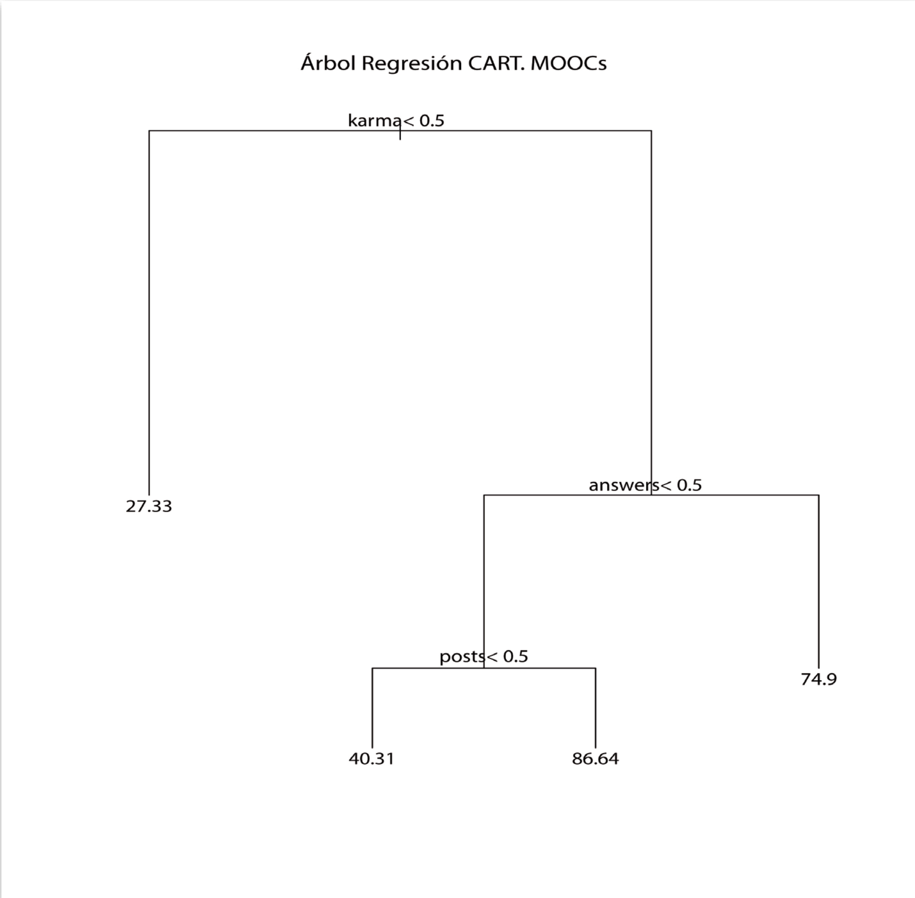
Node	**Split**	**n**	**Deviance**	**Y val**
1)	Root	3250	4696972.00	32.09754
2)	karma< 0.5	2475	3145793.00	27.32525*

3)	karma>=0.5	775	1314799.00	47.33806
6)	answers<0.5	651	1052407.00	42.08909
12)	posts< 0.5	626	981123.90	40.30990*
13)	posts>=0.5	25	19681.76	86.64000*
7)	answers>=0.5	124	150291.60	74.89516*
1)	Root	3250	4696972.00	32.09754
2)	karma< 0.5	2475	3145793.00	27.32525*
3)	karma>=0.5	775	1314799.00	47.33806
6)	answers<0.5	651	1052407.00	42.08909
12)	posts< 0.5	626	981123.90	40.30990*

Source: compiled by the authors. n= 3250. (*) denotes terminal node

Represented graphically in figure 1:

Figure 1. CART



Source: compiled by the authors

Carrying out an analysis of the tree obtained, it can be deduced that karma is the most predictive covariate of the response variable “progress_percentage”. The students’ having obtained at least one karma is definitive in the progress of the course. Also, the set with more than one answer has a predictive value of 74.9, while those which did not give any answer have a value of 42.1. That is, in an analysis of how students who take the course progress, those who do not obtain any karma are assigned a 27.33% probability of progressing, compared with 72.2% of students who will progress with a karma on their record. Those with karma (one or more) and also one or more answers are assigned a 79.9% chance of progressing in the course.

However, for the group of students with one or more karmas but no answers recorded, the probability of advancing in the course will be determined by the number of messages they participate in. Thus, when they don't have messages, their probability of progressing is 40.32%, while with at least one message recorded, their probability of progressing is greater, reaching 86.64%. Finally, and starting with the "answers" node, for those students who have no answer recorded, the student's having at least one message is definitive in the classification.

As such, the explanatory covariates of the response "progress in the course" are, in this order, karma, replies and messages.

To guarantee the statistical robustness of the analysis, Principal Component Analysis (PCA) is applied to the number of individuals (3,250 in our case), we take also the twelve v variables already indicated. Through PCA, we will be able to explain which of them create greater variation due to the original variables. In this case, the "progress_percentage" variable has been discarded for the analysis as is considered already dependent. We are going to try to describe the rest of the variables in observation through a few linear combinations of them.

Thus, we carry out a PCA by starting with the standardized data which correspond to the 3,250 course participants. Again using the statistical programming environment *R*, we obtain the scree diagram graph resulting from the analysis (figure 2), along with the eigenvalues obtained for each of the principal components λi (table 3):

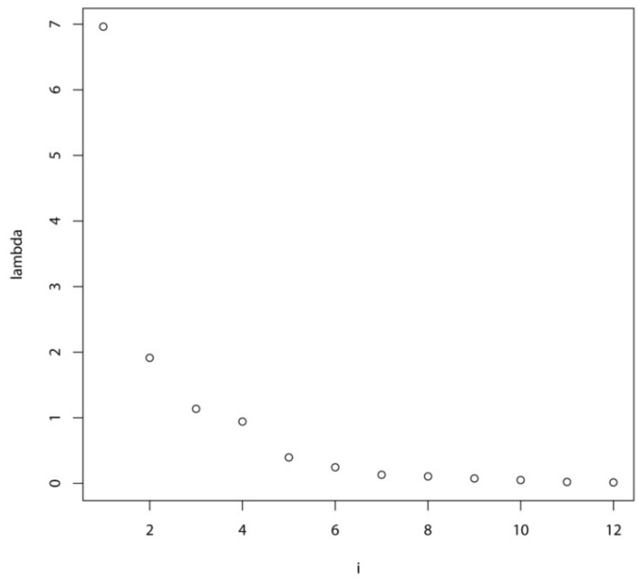
Table 3. PCA results

$\lambda 1$	6,964017 35	$\lambda 7$	0,13031514

λ2	1,91485725	λ8	0,1068764
λ3	1,13631158	λ9	0,07449995
λ4	0,94296705	λ10	0,05168136
λ5	0,39602074	λ11	0,02151268
λ6	0,24553626	λ12	0,01540423

Source: compiled by the authors

Figure 2. PCA Scree diagram



Source: compiled by the authors

After these calculations, we must determinate how many principal components will sufficiently explain our observation variables. An immediate solution (García Pérez, 2014) is to choose those that pick up more than 70% of the total variation and, in addition, come from standardized data, so that their associated eigenvalues are greater than 1. In this case, we deduce that, to get the accumulated variance to reach 70%, it is necessary to include the first two principal components. From the table 4 of eigenvectors (included as an appendix), we deduce that the two principal components to use will be:

$$CP1=0.21\ Z1+\ 0.23\ Z2+0.32\ Z3+\ 0.31\ Z4+\ 0.31\ Z5+0.27\ Z6+0.32\ Z7+0.32\ Z8+0.36\ Z9+0.05\ Z10+0.29\ Z11+0.35\ Z12$$

$$CP2=0.58\ Z1+\ 0.44\ Z2+0.07\ Z3-\ 0.24\ Z4-\ 0.26\ Z5+0.46\ Z6-0.04\ Z7-0.07\ Z8-0.10\ Z9-0.13\ Z10-0.26\ Z11-0.17\ Z12$$

The larger coefficient, of the first component is the one that corresponds to karma**.** In the case of the second principal component, we note the values of the coefficients which represent votes cast for posts, votes cast for answers and answers; that is, this second principal component represents the degree of students' participation in forums, voting on posts, voting on answers and answering. Afterwards, we establish the linear correlation between each of the variables and each of the specific principal components to more precisely analyze the importance of each variable in each of the principal components. In the first principal component, the variables karma and bronze badges have a correlation greater than 0.90, confirming that these recognitions obtained by students are the variables that influence it. In the second principal component, votes cast for posts presents a correlation of 0.80 and votes cast for answers has a correlation of 0.60, confirming that participation through votes cast by the student in the forum influences this component.

From all of this, we conclude that the student's completion of the course is tied to her degree of participation and rewards received, and particularly by the karma, according with her degree of interaction with the rest of the students.

Conclusions

The educational impact of MOOCs is still a new subject of research because this type of course is relatively new. Collaboration, interaction and a flexible attitude seems to be prerequisites for active learning in a changing and complex learning environment that sometimes lacks organized guidance.

Our contribution to this area of research is primarily driven by the interest of the results: first, a noteworthy result is the identification of the importance of participation and rewards received by the student, and especially of social reputation in participation with the community, which is something new and studied very little up to now. Second, the identification of karma as the more influential variable is an especially important discovery: it reinforces the relevance of the student's reputation, related to his contributions to the learning community. As we have noted, there is very little literature on the subject because the introduction of gamification techniques in the conception of on-line courses is recent, and references to MOOCs are remarkable.

Research on karma and the participation-reputation variable is very rare, and discussions about it are usually theoretical. As they have not been studied much, stressing the role of these variables entails a genuine result in this research and provides guidelines for the definition and design of these courses, not only for including factors that have proven to motivate the student, but also for incorporating tools that foster the behavior that the educators wish to strengthen (helping classmates, participating, etc.). Not in vain does gamification encourage participants to behave in certain ways (Hsu, Chang & Lee, 2013). As the lack of incentives is precisely one of the main challenges of MOOCs (Fini, 2009), rewards and reputation are "quick wins" which encourage, motivate and entertain. As stated by Fischer (2014) the challenges are to understand what drives motivation and interest, handling overloaded information and participation and changing the culture "have to learn" to "want to learn".

Finally, another relevant outcome of the analysis is to emphasize the importance of the correspondence of the student with her classmates, in the form of answers to or votes on the messages or answers from the rest of the students, as an explanatory factor in completing the course. This is why one of the conclusions of this study is that the completion of a MOOC course, and as such, success in the same, is directly and positively related to interaction among the students. These results also reinforces the idea that collaborative learning shapes up to be a methodology to follow in the design of MOOCs (Suárez & Gros, 2013), which are focused on more interactive teaching (Aparici & Silva, 2012).

Nonetheless, the study has some limitations, perhaps the most notable of which is the fact that it is a study based on a single MOOC (albeit with large amounts of data), which makes it difficult to generalize to other settings and types of students. However, this is normal in the context of MOOCs, where the use of a single MOOC to study the effectiveness of these courses is common in the literature (Greene, Oswald & Pomerantz, 2015; De Freitas, Morgan & Gibson, 2015). This is a widely-employed practice already identified by Liyanagunawardena et al. (2013) in their MOOC literature review.

As this is a pioneer study, the main difficulty we face is a lack of similar experiences for comparison. Fortunately, this will be corrected as research in this field increases. In any event, our results are relevant because they might help improve the conceptualization, design and success of future Massive Open Online Courses.

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APPENDIX

Table 4. PCA eigenvectors

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Votes for posts	0.21	0.58	0.05	-0.07	0.02	0.07	-0.43	0.18	-0.59	0.17	-0.10	0.09
Votes for answers	0.23	0.44	0.28	0.13	0.42	0.39	0.49	0.14	0.24	-0.08	-0.02	-0.02
Messages	0.32	0.07	0.27	0.14	-0.31	-0.68	0.39	0.17	-0.16	-0.14	-0.13	0.02
Messages with vote	0.31	-0.24	0.34	0.20	-0.13	0.15	0.06	-0.27	-0.12	0.62	0.40	-0.08
Total votes received	0.31	-0.26	0.31	0.23	-0.15	0.29	-0.28	-0.21	0.08	-0.26	-0.54	0.31
Answers	0.27	0.46	-0.06	-0.13	-0.17	-0.23	-0.28	-0.45	0.54	-0.05	0.18	-0.02
Answers with vote	0.32	-0.04	-0.45	-0.17	0.01	0.03	0.20	-0.14	0.00	0.35	-0.56	-0.41
Karma	0.32	-0.07	-0.47	-0.17	-0.02	0.08	0.26	-0.03	-0.09	0.02	0.19	0.73
Total votes	0.36	-0.10	-0.17	-0.01	-0.12	0.24	0.02	-0.11	-0.31	-0.59	0.34	-0.43
Gold medals	0.05	-0.13	0.42	-0.89	-0.01	0.05	0.07	-0.01	-0.03	-0.03	-0.03	0.01
Silver medals	0.29	-0.26	0.02	0.02	0.79	-0.40	-0.24	-0.08	-0.04	-0.05	0.05	0.00
Bronze medals	0.35	-0.17	-0.07	-0.03	-0.14	0.07	-0.28	0.75	0.39	0.10	0.12	-0.09

Source: compiled by the authors. Coefficients are rounded to two decimal places